

1 MORRISON & FOERSTER LLP
2 MICHAEL A. JACOBS (Bar No. 111664)
mjacobs@mofo.com
3 MARC DAVID PETERS (Bar No. 211725)
mdpeters@mofo.com
4 DANIEL P. MUINO (Bar No. 209624)
dmuino@mofo.com
5 755 Page Mill Road, Palo Alto, CA 94304-1018
Telephone: (650) 813-5600 / Facsimile: (650) 494-0792

6 BOIES, SCHILLER & FLEXNER LLP
7 DAVID BOIES (Admitted *Pro Hac Vice*)
dboies@bsflp.com
8 333 Main Street, Armonk, NY 10504
Telephone: (914) 749-8200 / Facsimile: (914) 749-8300
9 STEVEN C. HOLTZMAN (Bar No. 144177)
sholtzman@bsflp.com
10 1999 Harrison St., Suite 900, Oakland, CA 94612
Telephone: (510) 874-1000 / Facsimile: (510) 874-1460
11 ALANNA RUTHERFORD
12 575 Lexington Avenue, 7th Floor, New York, NY 10022
Telephone: (212) 446-2300 / Facsimile: (212) 446-2350 (fax)

13 ORACLE CORPORATION
14 DORIAN DALEY (Bar No. 129049)
dorian.daley@oracle.com
15 DEBORAH K. MILLER (Bar No. 95527)
deborah.miller@oracle.com
16 MATTHEW M. SARBORARIA (Bar No. 211600)
matthew.sarboraria@oracle.com
17 500 Oracle Parkway, Redwood City, CA 94065
Telephone: (650) 506-5200 / Facsimile: (650) 506-7114

18 *Attorneys for Plaintiff*
ORACLE AMERICA, INC.

19
20 **UNITED STATES DISTRICT COURT**
21 **NORTHERN DISTRICT OF CALIFORNIA**
22 **SAN FRANCISCO DIVISION**

23 ORACLE AMERICA, INC.

24 Plaintiff,
v.
25 GOOGLE, INC.

26 Defendant.

27 Case No. CV 10-03561 WHA
**DECLARATION OF IAIN M. COCKBURN
IN SUPPORT OF ORACLE AMERICA,
INC.'S OPPOSITION TO GOOGLE'S
MOTION TO STRIKE**

28
Dept.: Courtroom 8, 19th Floor
Judge: Honorable William H. Alsup

1 I, IAIN M. COCKBURN, declare as follows:

2 1. I have been retained by Oracle America, Inc. ("Oracle") as an expert in this matter. In
3 this declaration, at the request of counsel for Oracle, I address certain issues raised in Google's
4 Motion to Strike Portions Of Third Expert Report By Iain Cockburn And Expert Report By Steven
5 Shugan ("Motion to Strike") (Dkt. No. 720).

6 2. My background and qualifications, the terms of my retention, and the documents I
7 have reviewed are set forth in the report I submitted in this matter on February 3, 2012 (as revised
8 February 9, 2012) ("Cockburn Report"), and I incorporate them herein by reference. (See Cockburn
9 Report ¶¶ 8–10; App'x A, B.)

10 **My Use Of Certain Patent Value Distribution Curves In Connection With My "Group**
11 **And Value" Apportionment Analysis Was Reasonable**

12 3. Google claims that the three studies I used to evaluate the expected distribution of
13 value among the 569 patents included in the 2006 Bundle—the Harhoff,¹ Barney,² and PatVal³
14 studies—are inapplicable because they "have nothing to do with the Sun portfolio at issue" and "are
15 likely to have different distributions of value than the Sun portfolio." (Motion to Strike at 9–10.) In
16 my opinion, Google's criticisms are misplaced, and my use of these studies in my analysis was
17 appropriate.

18 4. As I explained at my deposition, it is my opinion that the distribution of value among
19 the 569 patents included in the 2006 Bundle would have been similar to the value distribution
20 reflected in these studies, which is also consistent with a number of other studies and my own
21 experience evaluating different patent portfolios, both in my academic work and in connection with
22 various licensing negotiations.

23
24 ¹ Harhoff D., F. Scherer, K. Vopel, "Citations, family size, opposition and the value of patent rights" Research Policy 32, October, 2002, pp. 1343-1363 ("Harhoff").

25 ² Barney, J. A., "A Study of Patent Mortality Rates: Using Statistical Survival Analysis to Rate and
26 Value Patent Assets," AIPLA Quarterly Journal, Vol. 30, No. 3, Summer 2002. ("Barney").

27 ³ Gambardella A., P. Giuri, and M. Mariani, "The Value of European Patents - Evidence from a
28 Survey of European Inventors," Final Report of the PatVal EU Project, January 2005 ("PatVal").

1 5. It is well-established and widely recognized that patent values are generally highly
 2 skewed, with a relatively small number of patents having significantly greater value. The three
 3 studies that I cited in my report each recognize this principle, and cite to other studies that confirm
 4 this same principle:

5 • “Consistently with previous findings in the literature, the economic value (measured in
 6 monetary terms) of the PatVal-EU patents is skewed: a small share of patents yields
 7 very high economic returns.” (PatVal, 2005, p. 5 (true and correct copy of article
 attached to this declaration as Exhibit A.));

8 • “The task of assessing the value of patent rights is a particularly difficult one, since the
 9 distribution of these values is highly skew. The skewness property has been discussed
 10 by numerous authors, e.g. Scherer (1965), Pakes and Schankerman (1984, p 79), Pakes
 11 (1986), and Griliches, 1990.” (Harhoff, 2003, p. 1344.);

12 • “[T]he model supports the view, long held by many in the field, that patent values are
 13 highly skewed. A relatively large number of patents appear to be worth little or
 nothing while a relatively small number appear to be worth a great deal.” (Barney,
 14 2002, p. 329.).

15 6. Many other studies reinforce this conclusion:

16 • “[T]he distribution of the value of patented innovations is known to be extremely skew
 17 implying that a few patents are very valuable, and many are worth almost nothing.”
 (Hall, 1999, p. 14.⁴);

18 • “This paper draws implications for technology policy from evidence on the size
 19 distribution of returns from eight sets of data on inventions and innovations
 20 attributable to private sector firms and universities. The distributions are all highly
 21 skew; the top 10% of sample members captured from 48 to 93 percent of total sample
 22 returns.” (Scherer, 2000 (true and correct copy of this article attached to this
 23 declaration as Exhibit B).⁵);

24 • “[I]n 1980 the top 10% of licensed technologies account for 95% of total gross
 25 income, and in 1990 the top 10% account for 88%. This feature of the distribution -
 26 that outlying tail values account for a large proportion of cumulative revenue - is
 27 consistent with previous evidence on the distribution of returns from industrial
 28 innovations (see Scherer and Harhoff 2000 for an excellent review), and university

⁴ Bronwyn Hall, “Innovation and Market Value,” NBER Working paper 6984, 1999.

⁵ Scherer, F. M. and D. Harhoff, “Technology policy for a world of skew-distributed outcomes,” Research Policy, v. 29, 2000, pp. 559-566.

inventions (Mowery et al. 2001; Mowery and Sampat 2001).” (Sampat and Ziedonis, 2005, pp. 285-286.⁶);

- “The distribution of the private value of patent rights is sharply skewed in all technology fields, with most of the value concentrated in a relatively small number of patents in the tail of the distribution.” (Schankerman, 1998⁷).

7. Google’s contention that a single-firm portfolio, such as the portfolio that I considered in this case, is “likely” to have a different distribution curve (Motion to Strike at p. __) is, in my opinion, incorrect. Google has not cited any study or paper in support of this proposition, and I know of none. In contrast, one study from 2000 shows that the patents of a single firm (Harvard) have a similar degree of skewness as the patents shown in the broader studies of both German and US patents, with the top 10 percent of each set capturing more than 80 percent of the value of that set.⁸

8. There have been a number of studies that focus on the distribution of value across various different patent populations, and they all come up with similar distribution curves. That includes published research that confirms the same highly skewed distribution for patents limited to specific product areas.⁹ Every paper I have reviewed suggests that the distribution of value of patent is highly skewed, and they confirm that the distribution curves that I used in my analysis for this case are reasonable.¹⁰ I would expect such similar distribution curves to apply to single-firm portfolios, including the one that I evaluated in this case.

9. My opinion in this respect is reinforced by the work that I did with a doctoral student, Ajay Agarwal, at University of British Columbia, who was studying patents licensed or offered for

⁶ Bhaven Sampat and Arvids Ziedonis, "Patent Citations and the Economic Value of Patents," Handbook of Quantitative Science and Technology Research 2005, Part 2, 277-298.

⁷ M. Schankerman, "How Valuable is Patent Protection? Estimates by Technology Field," *Rand Journal of Economics*, Vol. 29, 1998, pp. 77-107.

⁸ Scherer, F. M. and D. Harhoff, "Technology policy for a world of skew-distributed outcomes," *Research Policy*, v. 29, 2000, pp. 559-566.

⁹ Harhoff D., F. Scherer, K. Vopel, "Citations, family size, opposition and the value of patent rights" Research Policy 32, 2003, pp. 1343-1363.

¹⁰ See also, e.g., Gambardella A., P. Giuri, and M. Mariani, "The Value of European Patents - Evidence from a Survey of European Inventors," Final Report of the PatVal EU Project, January 2005.

1 license by the Massachusetts Institute of Technology. As I explained in my deposition, Dr. Agarwal
 2 studied licensing payments received by MIT for all of the patents in its portfolio. Such payments
 3 provide a basis for economic valuation based on received or projected licensing revenue, and the
 4 distribution of value within that single portfolio displayed the same property that I rely on in my
 5 report: a very small number of patents, 1-2%, commanded more than 50% of the value of the
 6 portfolio. That work is consistent with the Scherer article, and confirms that single-firm portfolios
 7 demonstrate similar value distributions as the larger samples reflected in other studies.¹¹

8 10. Additionally, as I explained in my deposition, I recently worked on a research project
 9 in which I reviewed licensing data collected for several thousand patents held by two large medical
 10 research centers. These portfolios owned by a specific institution again display the same
 11 phenomenon that is described in the Harhoff, PatVal, and Barney papers: the distribution of value in
 12 these single-company portfolios was highly skewed, in that a small number of patents had a
 13 substantially greater value than the rest of the patents. Even among those patents that were licensed, a
 14 handful constitute the vast majority of the value, and have been licensed or sold at a premium.

15 11. Based on my conversation with Alfonso Gambardella, the author of the PatVal study,
 16 the distribution of the value within the portfolios of individual companies is very similar to the
 17 distribution of value within the larger sample of patents in the published paper.

18 12. This phenomenon has been repeatedly described to me in the course of conversations
 19 and research interviews with licensing executives for large US-based technology companies,
 20 including IBM, United Technologies, and Pitney Bowes.

21 **My Calculation Of The Value of Copyrights Included In The 2006 Bundle Other Than**
 22 **The Infringed APIs Was Reasonable**

23 13. Google claims that I confuse cost with value based on my analysis of the copyrighted
 24 materials at issue in the 2006 Bundle, and argues that my analysis is therefore inadequate. (Motion to
 25 Strike at 13.) Google is wrong. The “millions of lines of code” that Google claims would have been

26
 27 ¹¹ Bhaven Sampat and Arvids Ziedonis, “Patent Citations and the Economic Value of Patents,”
 28 Handbook of Quantitative Science and Technology Research 2005, Part 2, 277-298

1 copyrighted in 2006 would not have any value to Google separate and apart from the code itself,
2 which I have fully accounted for in my assessment of the cost to write that code. As explained in my
3 report, I fully accounted for the copyrighted materials included in the 2006 Bundle but which are not
4 in-suit by calculating the full cost of developing that copyrighted code.

5 14. Google's patent damages expert, Dr. Leonard, uses the same proxy as I do to calculate
6 value. In Dr. Leonard's October 2011 report, he also used the cost of writing a certain amount of
7 code—the cost of building a virtual machine—which he pegs at approximately \$11 million. If there
8 is significant "value" on top of the pure code of a virtual machine, Dr. Leonard should have
9 accounted for such value in this calculation.

10 15. I have not confused cost and value. If there had been an agreement between the
11 parties, it might have cost Sun next to nothing to provide Google some of the source code Google
12 wanted for the Java virtual machine and associated libraries. However, given that all these items
13 provide value to Google, I calculate the value to Google as the cost of writing that code from scratch.
14 Effectively, the value is the avoided cost. By calculating the cost to Google of writing that source
15 code, I have fully accounted for the value to Google.

16 **The Conjoint Analysis**

17 16. I understand that Prof. Steven Shugan, who conducted a conjoint study to evaluate the
18 enhancements enabled by the use of the copyrights and patents that Google is alleged to have
19 infringed, has submitted a declaration in support of Oracle's opposition to Google's motion in which
20 he explains how Google's critiques of the conjoint analysis are badly misinformed. I have reviewed
21 Prof. Shugan's critiques, and I agree with them.

22 **The Econometrics Analysis**

23 17. Google claims that my econometric analysis should be excluded for two reasons.
24 First, Google claims that my analysis is based on unrepresentative data. Second, Google claims that
25 my calculation of market share is based on unreasonable assumptions about price and consumer
26 choices. Google is wrong on both points.

27 **A. My calculations are based on representative data.**

1 18. Google claims that eBay purchasers are not representative of purchasers in brick-and-
 2 mortar stores. Google's position that online sales data do not provide meaningful information about
 3 consumer preferences is contrary to Google's own practices. As a company, Google makes money
 4 by analyzing online consumer behavior and selling that information to firms interested in reaching
 5 potential consumers.¹²

6 19. Google has emphasized that it uses data from online purchases, rather than brick-and-
 7 mortar stores.

- 8 • Google has proposed a Google Price Index (GPI) based on online prices as an improved
 9 way of tracking inflation. Rather than waiting for answers from brick and mortar stores
 10 (as the U.S. government does in producing the CPI), GPI tracks inflation through online
 11 prices. Generally, Google's index and the U.S. Government's index closely track one
 12 another.¹³ An independent effort to use online price information to track pricing and
 13 inflation has found very similar results. MIT's Billion Prices Project's (BPP) uses online
 14 prices to construct a measure of inflation that tracks the Bureau of Labor Statistic's
 15 measure of the CPI very closely, suggesting that online prices have a close
 16 correspondence to those observed in traditional retail outlets.¹⁴
- 17 • Google Shopper searches the web (including the websites of both online and brick-and-
 18 mortar stores) to deliver the best prices for keyword-searched goods. It is difficult to
 19 reconcile Google's claim that consumers who buy their phones from eBay versus mobile
 20 carriers and brick and mortar stores are not linked when Google, itself, provides a shopper
 21 that allows consumers to compare prices between the two.¹⁵
- 22 • When Google commissions studies to better understand purchasing behavior, it has, itself,
 23 looked at eBay data. For example, eBay was among the sites analyzed in a study

24 ¹² Firms that advertise on Google include both brick and mortar and online firms.

25 ¹³ See, e.g., Robin Harding, *Google to map inflation using web data*, Financial Times, ft.com (Oct.
 26 11, 2010), available at <http://www.ft.com/intl/cms/s/2/deeb985e-d55f-11df-8e86-00144feabdc0.html#axzz1mvc6HBDa>; Alexis Madrigal, *Google Price Index Highlights Slowness of Economic Data Collection*, The Atlantic, (Oct. 12, 2010), available at <http://www.theatlantic.com/technology/archive/2010/10/google-price-index-highlights-slowness-of-economic-data-collection/64393/>; Tavia Grant, *Google eyes trends as economic indicators*, The Globe And Mail, (Oct. 12, 2010), available at <http://www.theglobeandmail.com/report-on-business/economy/google-eyes-trends-as-economic-indicators/article1754248/>.

27 ¹⁴ <http://bpp.mit.edu/usa/>

28 ¹⁵ See, e.g., <http://www.google.com/mobile/shopper/>

commissioned by Google to better understand consumer purchases of e-readers, netbooks, tablets, and laptops.¹⁶

20. Google's Chief Economist, Hal Varian, has even emphasized how useful eBay data could be for economic use. Indeed, as the two examples below make clear, Dr. Varian clearly endorses the use of eBay data to understand consumers' willingness to pay for products they demand. Dr. Varian's biggest concern appears to be that because bidders seem reluctant to use eBay's automated "bidding agent" that is intended to eliminate any incentive for late bidding, eBay data leads to an underestimate of consumers' willingness to pay (e.g., Dr. Varian seems to believe that my econometric analysis is an appropriate way to conservatively estimate consumers' willingness to pay).

- Dr. Varian has used online data from eBay to test his own theories. In a New York Times article,¹⁷ he wrote: “Online auctions offer a wonderful laboratory for experimental economists: the participants are intelligent adults, spending real money, who hope to purchase goods in which they have an intense interest. This is a far cry from the reluctant sophomores whom experimentalists have had to rely on in the past to test economic theories. Analysis of online auction data has yielded a wealth of insights, and a few puzzles. A particularly intriguing puzzle has been the tendency for ‘late bids.’ In a representative sample of eBay auctions, researchers found that 37 percent of them exhibited bids in the last minute and 12 percent had bids in the last 10 seconds. These data underestimate the actual number of bids submitted in the closing seconds of the auction, since bids that arrived at eBay after the auction had closed were not counted. The late-bid puzzle is particularly interesting, since eBay offers an automated “bidding agent” that is intended to eliminate any incentive for late bidding. I only need to tell my bidding agent the most I am willing to pay for an item, along with my initial bid. If someone bids more, my agent will automatically increase my bid by the minimal bid increment, as long as this doesn’t raise my bid over my maximum. In theory, each bidder should report his true maximum willingness to pay and let the agent do the work of bidding. In the end, the person with the highest willingness to pay for the item will win the auction, paying a price equal to the second-highest willingness to pay plus the bid increment.”

¹⁶ See, e.g., Google.com, *Portable PC Shopper*, October 2010, available at <http://www.thinkwithgoogle.com/insights/library/studies/portable-pc-shopper/> Among the paper's conclusions are that shoppers looking for e-readers, netbooks, tablets, and laptops check the following different sites when shopping: Amazon, eBay, Sam's Club, Best Buy, Fry's, Staples, Circuit City, Newegg, Target, Comp USA, Office Depot, Tiger Direct, Costco, Office Max, Walmart, CDW, Radio Shack. *See id.* at p. 38.

¹⁷ Hal Varian, *Online auctions as a laboratory for economists to test their theories*, New York Times (Nov 16, 2000), available at <http://people.ischool.berkeley.edu/~hal/people/hal/NYTimes/2000-11-16.html>

1 • Dr. Varian has also written a chapter in a microeconomics textbook discussing auction
 2 design that discusses how in a Vickrey auction (which eBay's proxy bidder system
 3 effectively is), it is in the bidder's interest to submit his or her true willingness to pay.¹⁸

4 21. In addition to being contrary to its own business practices, Google's suggestion that
 5 the econometric analysis is based on unrepresentative data is incorrect for a number of reasons.

6 22. First, this criticism misunderstands the purpose of the econometric analysis. I
 7 analyzed eBay data not to model *the price* at which OEMs or mobile carriers sell smartphones to their
 8 customers, nor to measure the discount that a used or unlocked smartphone sells at compared to a
 9 new smartphone. In either of these scenarios, the difference in price point between an unlocked, used
 10 phone and a new phone bundled with a carrier plan might have some significance, because the
 11 analysis would be sensitive to differences between the two populations. However, that was not the
 12 purpose of my analysis. Instead, I measured how consumers value the *incremental benefit of*
 13 *features*, particularly performance and speed. I therefore tested an eBay purchaser's incremental
 14 willingness to pay for an incrementally faster phone against the same population's incremental
 15 willingness to pay for an incrementally slower phone. The difference is important, because the
 16 population I analyzed was held constant. The only question one needs to ask is whether there is any
 17 reason to suppose the incremental value that online purchasers place on these features is any more or
 18 less than the incremental value of purchasers who buy in traditional in-store sales outlets. There is, in
 19 fact, no reason to suppose there are any meaningful differences, nor have I seen Google offer any
 20 evidence to the opposite.

21 23. Second, Google's criticism of the representativeness of eBay data ignores the role of
 22 resellers in the eBay data. Resellers, who either purchase their stock on eBay or use eBay as a outlet
 23 to sell stock purchased elsewhere, provide a link between eBay and other channels for purchase.
 24 These resellers, in order to make a profit, must reflect end consumers' preferences. It is a well-
 25 established proposition in economics that the ability to arbitrage across customer subgroups makes it

26
 27

¹⁸ Varian, H. R., *Intermediate Microeconomics: A Modern Approach*, Seventh Edition, pp. 315-316.
 28

impossible for firms to differentially price across the subgroups.¹⁹ In other words, this ability (and potential for) arbitrage leads to one price, regardless of where or how a consumer purchases a product.²⁰ Google fails to understand this fundamental link. Instead, Google suggests that my results are unreliable because I base them on data which includes resellers. Thus, Google's criticisms—on the one hand, criticizing eBay data for being unrepresentative and on the other hand, criticizing the inclusion of resellers—are inconsistent and show little understanding of how markets work.²¹

24. Third, Google's concerns regarding the inclusion of used phones in the eBay data is not well-grounded. Google fails to recognize the important economic relationship between new and used goods. Exactly the same models of phones are sold on eBay as are sold in physical stores, whether in new condition, used, factory reconditioned, or otherwise. There is a long literature in economics and business that teaches us that there are strong relationships between new and used goods.²² This is true whether new and used goods are sold in the same channels or through different

¹⁹ “Under arbitrage, a consumer who is offered a lower price for a good by a firm purchases an excess quantity of the good and resells the good to consumers who are denied the lower price by the firm. Under perfect arbitrage, the firm would be forced to sell all its output at the lowest price to consumers offered the lowest price, who would then resell to other consumers. Thus, arbitrage effectively turns price discrimination into offering a single price.” Preston MacAfee, “Price Discrimination,” *Issues in Competition Law and Policy*, Volume I (ABA Section of Antitrust Law 2008), p. 467. See also: Hal Varian, “Price Discrimination,” Chapter 10, *Handbook of Industrial Organization*, Volume I, Edited by R. Schmalensee and R.D. Willig, Elsevier Science Publishers B.V., 1989, p. 599 and Jean Tirole, *The Theory of Industrial Organization*, MIT Press, 1988, pp. 134-135.

²⁰ In economics, this is referred to as the “Law of One Price” – which demonstrates that in a competitive market, all transactions between buyers and sellers occur at a single, common market price. Preston MacAfee, *Price Discrimination, Issues in Competition Law and Policy*, Volume I (ABA Section of Antitrust Law 2008), p. 467. See also: David Besanko and Ronald R. Braeutigam, *Microeconomics* (4th edition), Wiley, 2010, at p. 331.

²¹ As Dr. Leonard noted, several bidders bid on many auctions – probably with the objective to resell these phones. Furthermore, many sellers on eBay operate on several electronic stores—such as eBay, Amazon Marketplace, and Buy.com. Some eBay sellers operate both in their own electronic stores or in brick-and-mortar stores. The evidence of the many linkages between eBay and more traditional distribution channels – electronic or not – can only lead to one conclusion: the law of one price will prevail thanks to arbitrage.

²² See, for example, “Exploring the Relationship between the Markets for New and Used Durable Goods: The Case of Automobiles. Devavrat Purohit. *Marketing Science* Vol. 11, No. 2 (Spring, 1992), pp. 154-167. ; Benjamin D, Kormendi R. “The Interrelationship between Markets for New and Used Durable Goods,” *Journal of Law and Economics*, October 1974, 17(2):381-401.

1 channels, as they are in this case.²³ Google also claims that whether or not a phone is locked to a
 2 particular carrier is a significant issue. Again, it is important to note that the same models of phone
 3 are sold locked and unlocked in traditional outlets as well as on-line, and purchasers can always
 4 unlock the phone themselves or have this done for them at a nominal fee. Prices of locked and
 5 unlocked phones are therefore closely related. In any case, although there may be some differences
 6 between the prices of new versus used or locked versus unlocked phones, Google fails to recognize
 7 that my econometric analysis explicitly accounts for whether a phone is new or used and whether a
 8 phone is locked or unlocked.²⁴ The econometric modeling will absorb any systematic differences, if
 9 they exist. Yet, Google fails to acknowledge these facts.

10 **B. My calculations are not based on any unreasonable assumptions.**

11 25. Google claims that my calculation of market share is based on unreasonable
 12 assumptions about price and consumer choices. First, Google claims that contrary to my assumption,
 13 the price of Android phones wouldn't have remained unchanged in a but-for world in which Android
 14 phones would be slower. Second, Google claims that my choice of a ten-day window to observe bids
 15 leads to an overestimate of the number of people who would not have bought the slower Android
 16 phone. Neither one of these critiques has merit.

17 **1. The assumption that the price of Android would remain constant is reasonable.**

18 26. Google claims that my assumption that the price of Android phones would have
 19 remained unchanged in a but-for world is incorrect and that it leads to an overestimate of damages.
 20 Google's apparent logic is that in a world in which Android phones were slower and performed more
 21 poorly, the price of Android phones would have declined. This is an alternative assumption to the
 22 way I conduct my primary analysis. In making this argument, Dr. Leonard and Google completely
 23 ignore the obvious implication that any decline in prices of Android phones due to the reduced

25 ²³ Again, we expect the law of one price to hold, regardless of channel. See, for example, Shulman,
 26 Jeffrey D., Coughlan, Anne T. "Used goods, not used bads: Profitable secondary market sales for
 durable goods channel," Quant Market Econ, (2007) 5:191–210, June 5, 2007.

27 ²⁴ As I explained in Appendix C to my February 3, 2012 report, I include controls for whether a
 28 phone is used or new, and whether a phone is locked or unlocked.

1 quality of the operating system itself is not irrelevant in measuring the reasonable royalty due to Sun.
2 Quite the opposite – this price decline itself is one such measure.

3 27. I have considered and discussed this possibility in my report. In Exhibits 6-9 I have
4 discussed the change in users' willingness-to-pay for Android phones with diminished performance.
5 For example, I have determined that disabling the '104 patent would translate into a decrease in
6 users' willingness-to-pay of \$24-\$29 (Exhibit 6). Presumably, if the price of Android phones
7 decreased by that amount in the absence of features enabled by the '104 patent, sales of Android
8 phones would remain unchanged.

9 28. In that case, one has to consider how this price differential would be financed. The
10 wireless industry is intensely competitive. Android OEMs and carriers compete with very similar
11 products and therefore likely earn small margins. If these companies were forced to reduce price by
12 \$24-\$29 to compensate for lower quality of the Android OS , they would require Google to
13 compensate them, for example through additional technical assistance or (increased) revenue sharing
14 or both. In the end, it would be Google's burden to absorb the majority, if not all, of the price
15 decline, or face the likely failure of Android. Therefore, I conclude that Google would have been
16 willing to pay a patent royalty to Sun in the amount up to the decrease in the users' willingness-to-
17 pay. For the case of the '104 patent, Google would be willing to pay Sun up to \$29 per unit. The
18 upper bound of my calculated royalty rate for the '104 patent is just \$2.36 (see Exhibit 12b) – over 10
19 times less than this measure of Google's willingness-to-pay for that technology. This confirms that
20 my analysis of royalty rates is reasonable and conservative.

21 **2. My assumption that the ten-day window to observe bids is representative is
22 reasonable.**

23 29. Google next claims that my choice of a ten-day window to observed bids leads to
24 overestimate the number of people who would not purchase a smartphone. This claim is wrong. It
25 betrays a fundamental misunderstanding of my model.

26 30. Google ignores the fact that the computation of the number of buyers who would
27 switch away from Android phones is not tied to a particular auction, but compares bidders' revealed
28 valuations to the prevailing average prices for the phones on which they bid.

1 31. In my model, individual bidders' valuations of the slower phones are compared to the
 2 average price of that phone. If the price is higher than the bidder's valuation he simply doesn't buy
 3 that phone. Contrary to what Google claims, this bidder will *not* go to AT&T or Verizon to buy the
 4 same phone: that slower phone is simply too expensive relative to that bidder's valuation for them to
 5 be willing to buy it, whether it is sold on eBay, by a wireless carrier, or in a brick-and-mortar store.

6 32. Finally, Google contests my conclusion that 15% of Android phone buyers in 2010
 7 wouldn't have acquired a smartphone at all if the Android phones had been dramatically slower.
 8 Google's critique is unrealistic, misguided and shows a fundamental misunderstanding of my market
 9 share calculations. In fact, in 2009, almost 80% of wireless subscribers in the United States used
 10 feature phones, not smartphones, and the majority of US phones today still are feature phones.²⁵
 11 Stated differently, my results imply that, if Android phones had performed less well, consumers
 12 would have been slower to switch from their cell phones to smartphones, or alternatively, would have
 13 been slower to upgrade their smartphone to a newer model. This is hardly a surprising finding. To
 14 put it in context, in the but-for world I construct, I find that the sales of smartphones in the United
 15 States would have increased from 46 to 101 million units between 2009 and 2011, instead of the
 16 actual increase from 46 to 107 million units, a reduction of 5.5% of overall smartphone sales. My
 17 model estimates that sales of Android smartphones in the but-for world would still have increased
 18 from 4 to 22 million units instead of the actual increase of 4 to 46 million units. My model is also
 19 conservative based on my assumption that Android did not increase the overall size of the
 20 smartphone market. These estimates are hardly "unreasonable" as Google alleges.

21 **C. Google's own expert, Dr. Leonard, makes elementary errors in his econometric
 22 analysis.**

23 33. Upon close analysis, it is Google's expert Dr. Leonard, not I, who has made
 24 elementary mistakes in his econometric analysis. I only describe those errors briefly here, but it is
 25
 26

27 25 See <http://blog.nielsen.com/nielsenwire/consumer/smartphones-to-overtake-feature-phones-in-u-s-by-2011/>; <http://gigaom.com/2011/09/01/four-in-ten-u-s-phones-are-now-smartphones/>

1 my opinion that his analysis is flawed and unreliable, and his criticisms of my approach
 2 fundamentally erroneous.

3 34. First, Dr. Leonard falsely insists that the results from his Android-only model are
 4 meaningful. Yet, Dr. Leonard must know that by restricting his sample to only the 13 Android phone
 5 models he is unable to estimate the impact of more than twenty different smartphone features, as he
 6 claims to do. Mathematically, one simply cannot do this. The problem arises because there is
 7 insufficient variation in these features across the small number of phone models in Dr. Leonard's
 8 restricted sample. Dr. Leonard's "work-around" is to rely on the econometrics software package to
 9 arbitrarily drop certain features from the analysis. One result of this "work-around" is that the
 10 contribution of these omitted features to valuation "loads" on features that are retained, making those
 11 estimates unreliable. Furthermore, the result of this "work-around" is that Dr. Leonard's model is
 12 nearly collinear, and displays the familiar symptoms of near collinearity.²⁶ In these circumstances,
 13 his estimated coefficients are not reliable and are economically meaningless. Further, Dr. Leonard's
 14 "results" are not based on the variability in phone features (which would provide meaningful results);
 15 rather, his "results" are based on the different timing of auctions (which does not provide meaningful
 16 results).

17 35. Second, Dr. Leonard wrongly insists that multicollinearity only affects standard errors.
 18 ²⁷ This is nonsense; multicollinearity or near multicollinearity is generally recognized to also make

22 ²⁶ Greene provides an excellent summary of the current understanding of near-multicollinearity:

23 "When the regressors are highly correlated, we often observe the following problems:

- 24 • Small changes in the data can produce wide swings in the parameter estimates.
- 25 • Coefficients may have very high standard errors and low significance levels even
 though they are jointly highly significant and the R^2 in the regression is quite high.
- 26 • Coefficients will have the wrong sign or an implausible magnitude".

27 (Greene, William H. (1997): *Econometric Analysis*, 3rd edition, London, Prentice Hall, p. 420).

28 ²⁷ Note that I do not calculate standard errors formulaically from the regression estimates, but instead
 report "boot-strapped" standard errors which are much less sensitive to the impact of
 multicollinearity.

1 parameter estimates highly sensitive to small changes in sample or specification.²⁸ This is
 2 particularly true in non-linear models which are estimated here.

3 36. Third, Dr. Leonard insinuates that he ran a “Chow test.” I note that the Chow test per
 4 se is only appropriate for use on linear models; yet, both my model and Dr. Leonard’s version of my
 5 model are nonlinear models. If Dr. Leonard, in fact, used an analogue appropriate to this context, he
 6 has cited the wrong paper.²⁹

7 37. Fourth, Dr. Leonard makes deceptive claims about the stability of estimated
 8 coefficients in different subsets of the data. Because the specification of the model, that is to say the
 9 list of explanatory variables, is not held constant across the different subsets of the data that Dr.
 10 Leonard considers (there is no or insufficient variation in some variables within subsets of the data),
 11 his analysis conflates the effect, if any, of variation over time in the economic relationship between
 12 valuations and the explanatory variables with the effect of changing the set of explanatory variables.
 13 For example, Dr. Leonard claims to observe variation in the Linpack coefficient for different time
 14 periods. Yet, the evidence Dr. Leonard presents is generated from models which severely limit the
 15 size of the sample used and therefore the set of models present in each subset. As it happens, in some
 16 of Dr. Leonard’s monthly regressions, there are simply no Android phones; in others there are only a

17
 28 There are two types of near-multicollinearity. The first results from high correlation among
 18 regressors (structural issue.) The second is numerical. The regressor data matrix is ill-conditioned.
 19 This problem gives rise to erratic volatility. As Spanos and Guirk explain:

20 The presence of ill-conditioning in (XTX) indicates that the sample information is ‘nearly-
 21 insufficient’ for reliable inference concerning X . In such a case the modeler should answer the
 22 question whether he/she can live with the potential erratic volatility as quantified by the norm
 23 bounds. If not, the only obvious way to proceed is to ameliorate the sample information in an
 24 attempt to render the data matrix well-conditioned. In the case of observational data this
 25 amounts to changing the units of measurement and/or getting additional or better quality data;
 26 see Silvey (1969). In the case of experimental data repeating or re-designing the experiment
 27 are additional potential options. (Spanos, A. and McGuirk A. (2002): The Problem of Near-
 28 Multicollinearity Revisited: Erratic vs Systematic Volatility, Journal of Econometrics, Vol.
 108, pp. 365-393.)

Dr. Leonard’s analysis violates this well-established principle. Rather than using the existing well-designed and acceptable sample, he divides the sample into sub-samples that suffer from erratic volatility.

²⁹ Again, by reducing the sample artificially, Dr. Leonard generates subsamples with ill-conditioned regressor matrices. The fact that his so-called Chow test concludes that the subsamples are not identical only proves that the subsamples are unreliable.

1 few smartphones overall. During the time period covered by my analysis, many new models were
2 introduced, and during any specific month not all models will be present in the data. Further, Dr.
3 Leonard should know to attempt to measure 11 unique phone features in a month in which there are
4 data for only five phones is impossible. As with his analysis of an Android-only subset of the data,
5 by reducing the sample artificially, Dr. Leonard again generates subsamples with ill-conditioned
6 regressor matrices, which, in turn, lead to unreliable and highly unstable estimates. Contrary to Dr.
7 Leonard's claim, his results simply do not support his claim that my requiring coefficients be equal
8 across months is incorrect.

9 38. Fifth, Dr. Leonard wrongly claims that any bias in some coefficient estimates is
10 necessarily transmitted to other coefficient estimates. The extent of any such "contamination" is an
11 empirical question. Dr. Leonard offers no evidence to this point.

12 39. Sixth, Dr. Leonard further alleges that I made a comparison between his Android-only
13 model and my revised Android-only specifications based on the Schwartz criterion (Dr. Leonard
14 supplemental report, p. 12). I made no such comparison in my report. Dr. Leonard focuses on this
15 imaginary comparison instead of addressing the very valid concerns I presented related to collinearity
16 in both my rebuttal and 3rd damages report. On these substantive issues Dr. Leonard remains silent.

17
18 I declare under penalty of perjury that the foregoing is true and correct and that this
19 declaration was executed on February 24th, 2012 at Boston, Massachusetts.

20
21 DATED: February 24, 2012

/s/ Iain M. Cockburn

22
23
24
25
26
27
28
IAIN M. COCKBURN

1 ATTESTATION OF FILER

2 I, Steven C. Holtzman, have obtained Dr. Iain Cockburn's concurrence to file this document
3 on his behalf.

4 Dated: February 24, 2012

5 BOIES, SCHILLER & FLEXNER LLP

6 By: /s/ Steven C. Holtzman
Steven C. Holtzman

7 *Attorneys for Plaintiff*
8 ORACLE AMERICA, INC.

9
10
11
12
13
14
15
16
17
18
19
20
21
22
23
24
25
26
27
28

BOIES, SCHILLER & FLEXNER LLP
OAKLAND, CALIFORNIA